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(54) **SYSTEM FOR INFORMATION DISCOVERY IN VIDEO-BASED DATA**

(75) Inventors: **Valerie Guralnik**, Mound, MN (US); **Kirk Schloegel**, Minneapolis, MN (US); **Petr Cisar**, Ceske Velenice (CZ)

(73) Assignee: **Honeywell International Inc.**, Morristown, NJ (US)

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G06F 17/30 (2006.01)

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(58) **Field of Classification Search** 707/749, 707/803, 737; 382/118; 348/563
See application file for complete search history.

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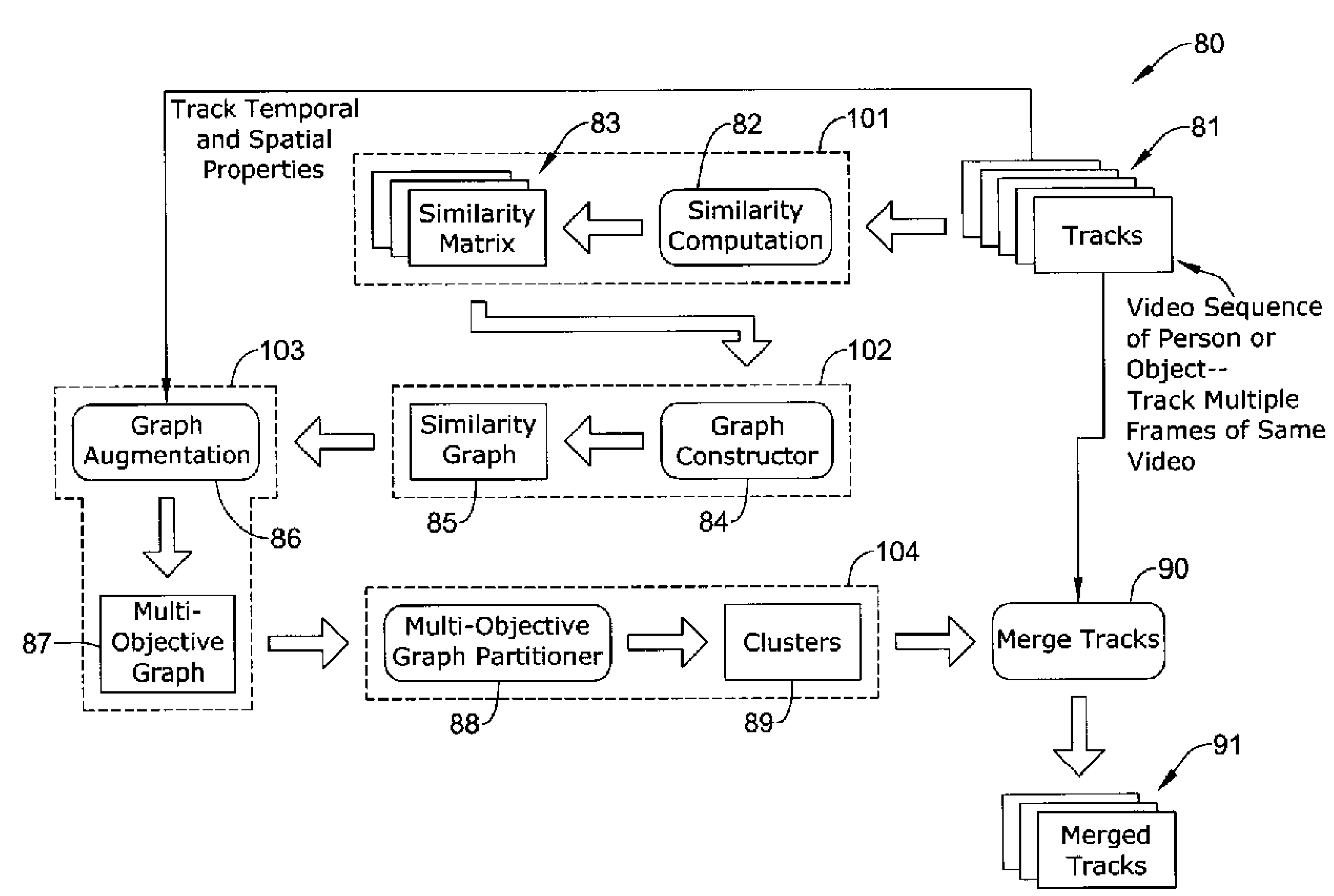
Primary Examiner — Cam Truong
(74) *Attorney, Agent, or Firm* — Seager Tufte & Wickhem LLC.

(57) **ABSTRACT**

A system for information discovery of items, such as individuals or objects, from video-based tracks. The system may compute similarities of characteristics of the items and present the results in a matrix form. A similarity portrayal may have nodes representing the items with edges between the nodes. The edges may have weights in the form of vectors indicating similarities of the characteristics between the nodes situated at the ends of the edges. The edges may be augmented with temporal and spatial properties from the tracks which cover the items. These properties may play a part in a multi-objective presentation of information about the items in terms of a negative or supportive basis. The presentation may be partitioned into clusters which may lead to a merger of items or tracks. The system may pave a way for higher-level information discovery such as video-based social networks.

5 Claims, 10 Drawing Sheets



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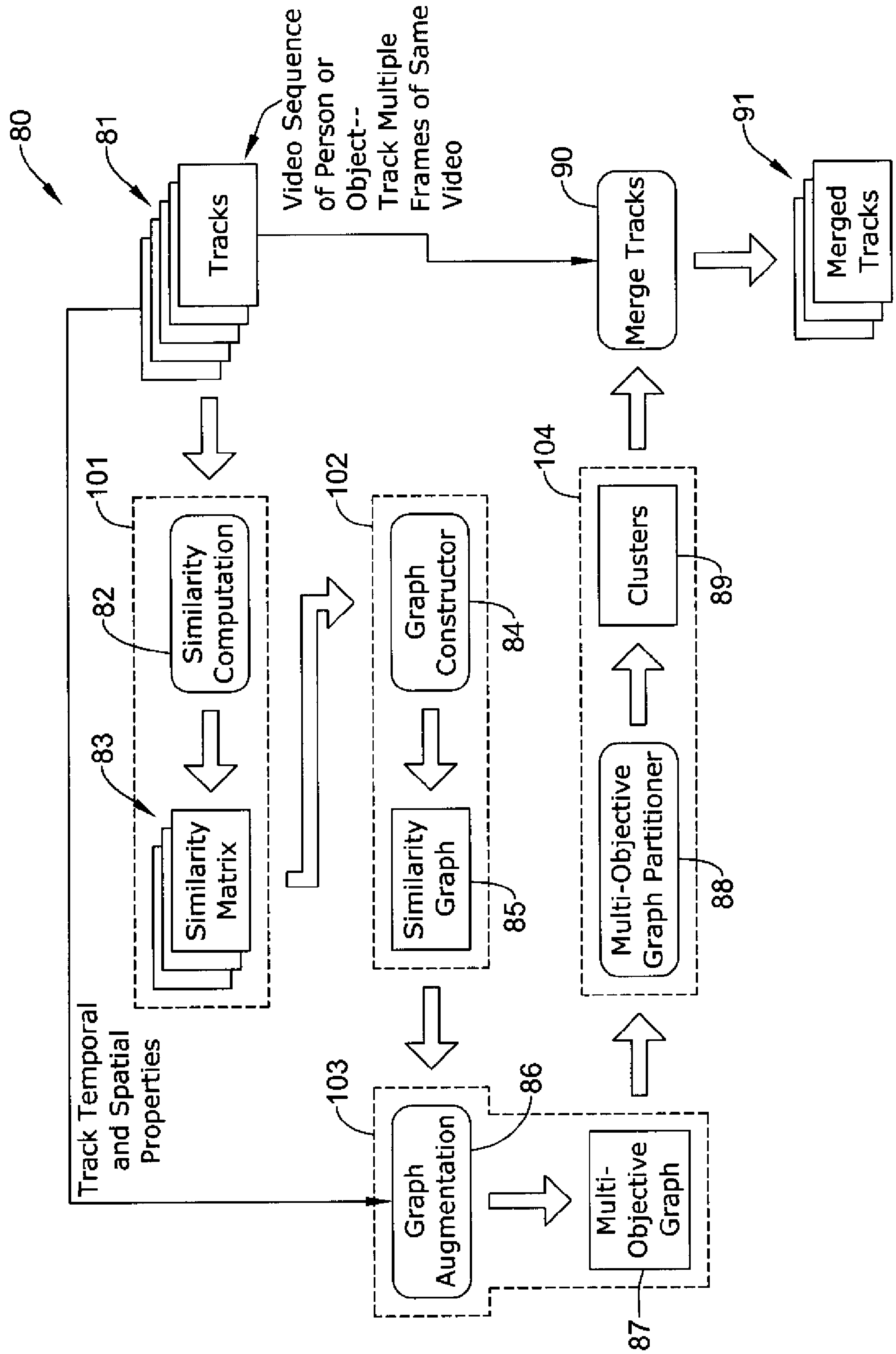
80
81
Tracks
Video Sequence of Person or Object-- Track Multiple Frames of Same Video
90
Merge Tracks
91
Merged Tracks
101
Similarity Computation
82
83
Similarity Matrix
102
Graph Constructor
84
Similarity Graph
85
104
Clusters
89
Multi-Objective Graph Partitioner
88
Track Temporal and Spatial Properties
103
Graph Augmentation
86
Multi-Objective Graph
87

Figure 1

83

	P1	P2	P3	P4	P5	P6	P7	P8	P9	•••
P1	1	.8	.5	.2	.4	.9	.7	.3	.6	
P2	.2	1	.0	.5	.8	.1	.6	.4	.7	
P3	.7	.5	1	.2	.6	.4	.9	.1	.3	
P4	.8	.1	.4	1	.3	.2	.0	.5	.6	
P5	.3	.6	.9	.4	1	.5	.7	.1	.2	
P6	.9	.8	.3	.7	.1	1	.2	.0	.4	
P7	.4	.6	.7	.9	.3	.5	1	.3	.8	
P8	.8	.0	.2	.6	.2	.9	.7	1	.5	
P9	.7	.6	.1	.0	.8	.0	.4	.9	1	
•••										

Figure 2

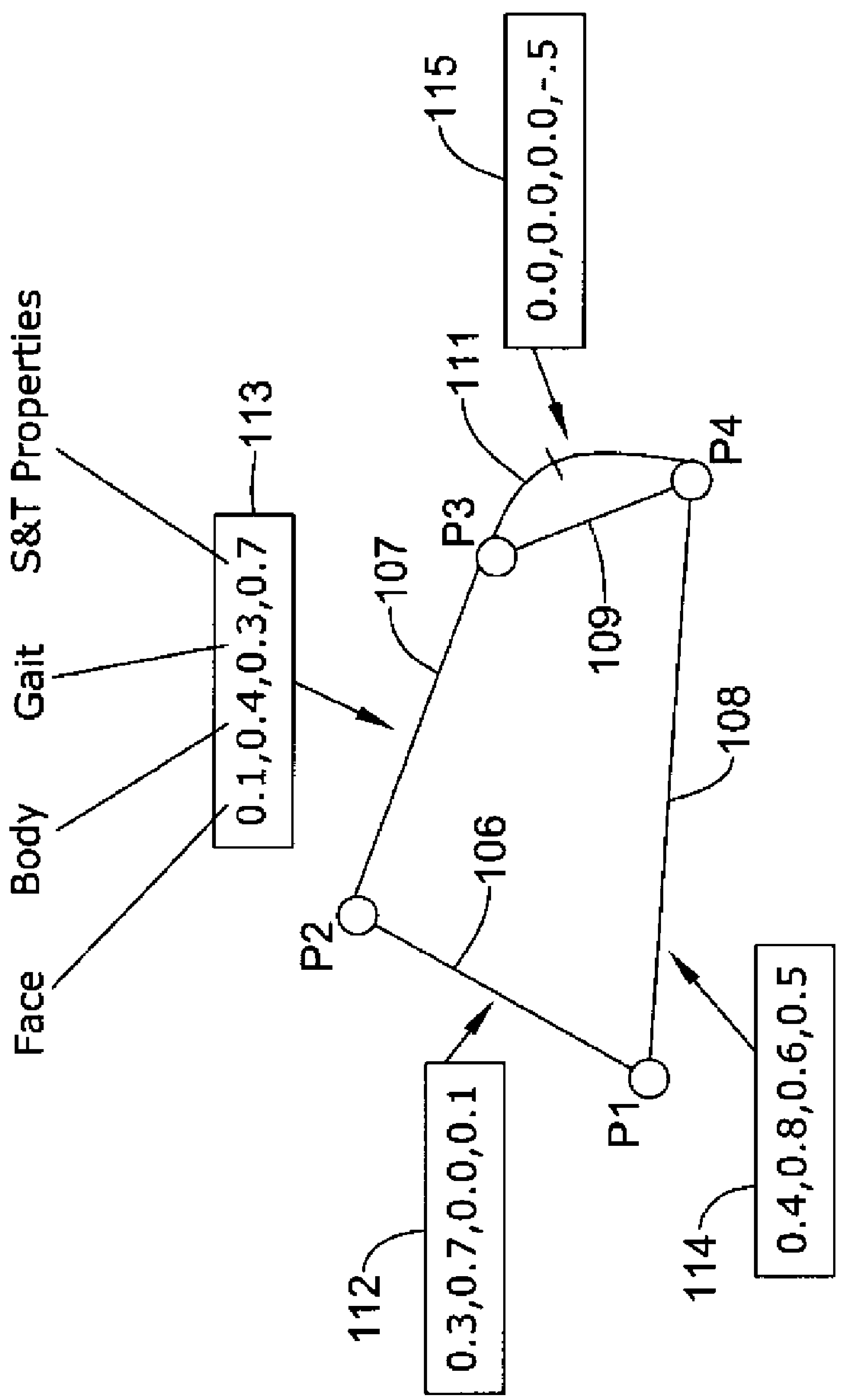
Face
Body
Gait
S&T Properties
113
0.1,0.4,0.3,0.7
115
0.0,0.0,0.0,-.5
111
P3
P4
107
109
108
106
P2
P1
112
0.3,0.7,0.0,0.1
114
0.4,0.8,0.6,0.5

Figure 3

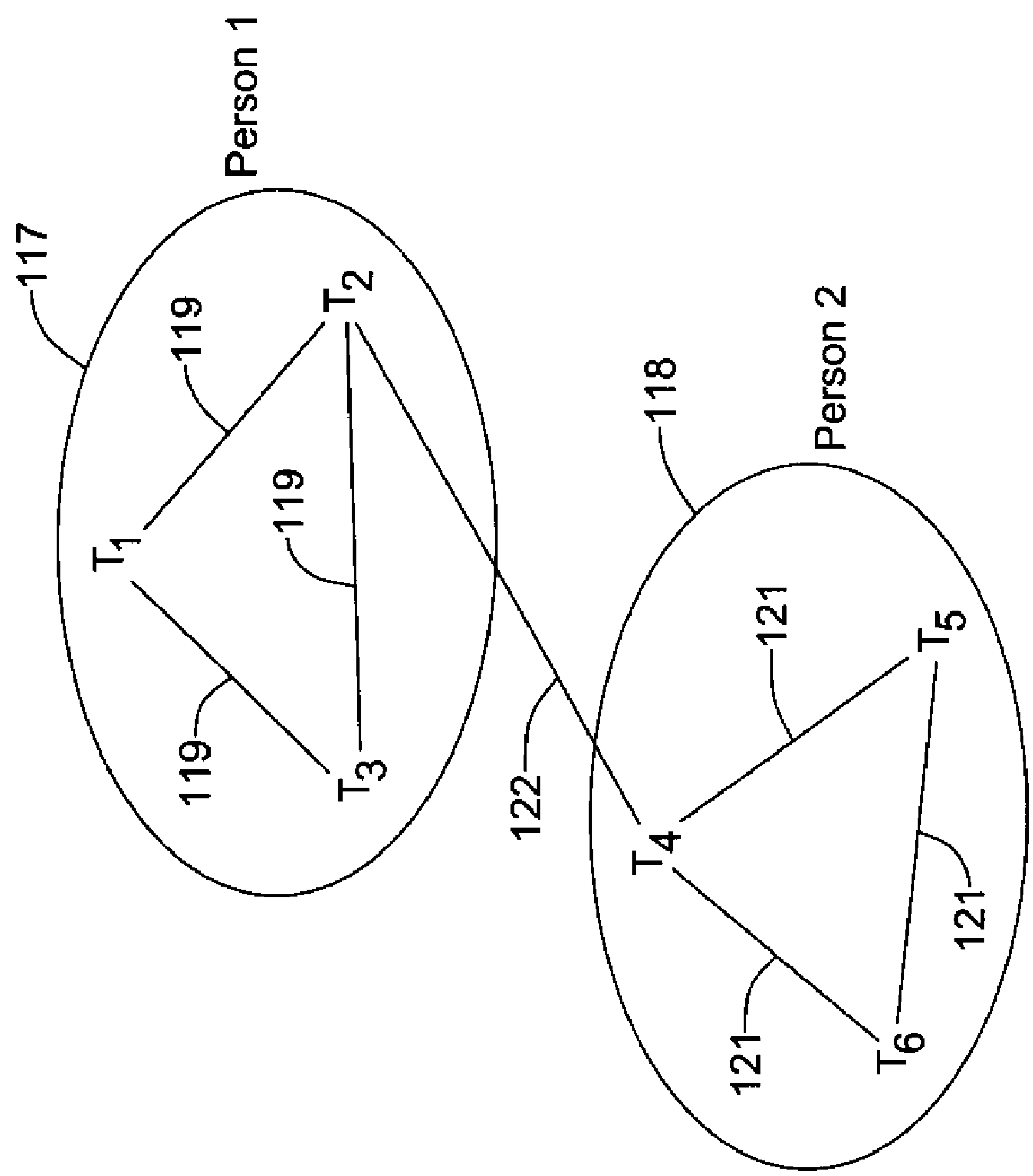
Person 1
117
119
T_1
T_2
119
119
T_3
Person 2
118
122
121
T_5
T_4
121
121
T_6

Figure 4

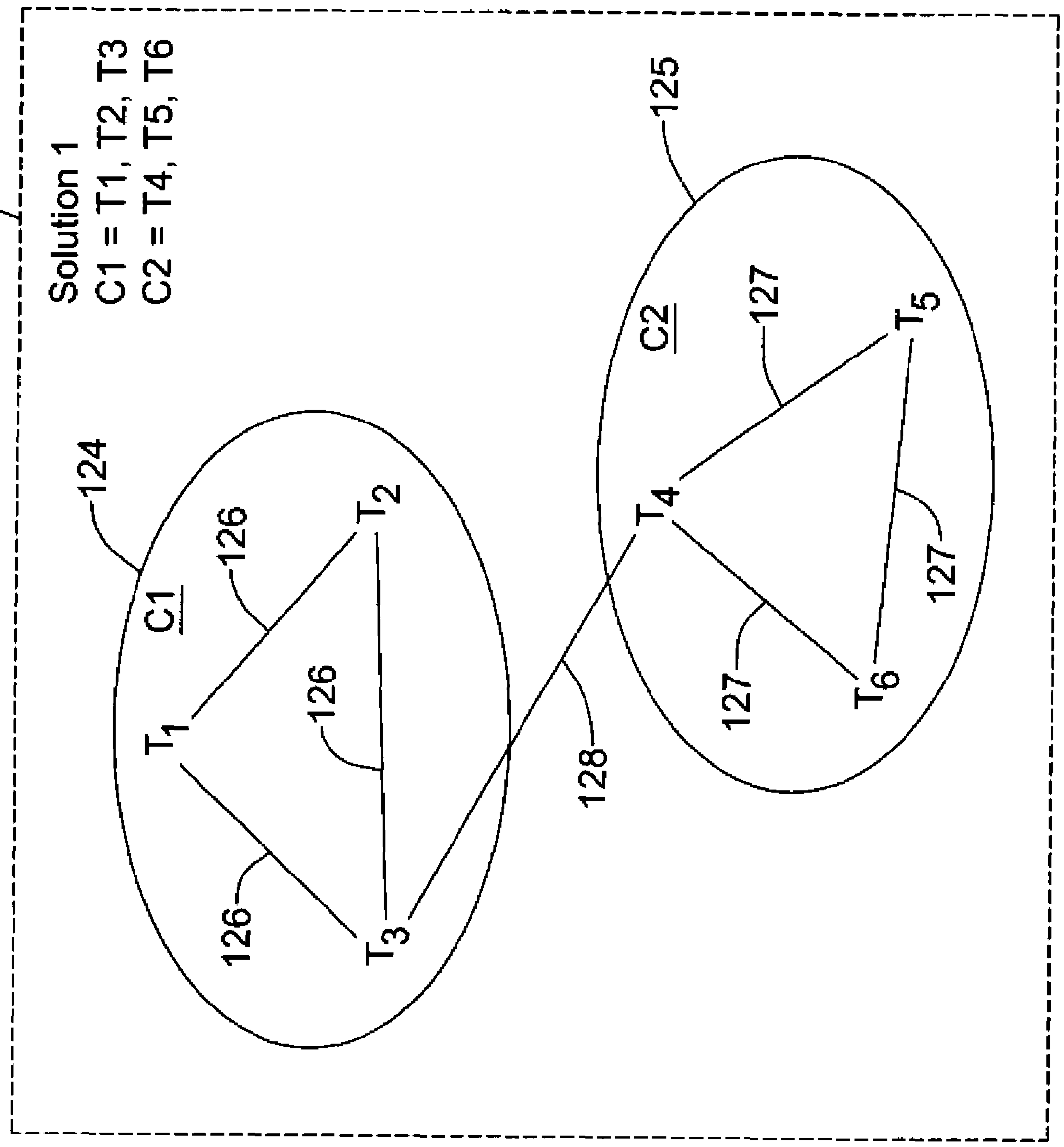
123
Solution 1
C1 = T1, T2, T3
C2 = T4, T5, T6
124
C1
T1
T2
T3
126
126
126
125
C2
T4
T5
T6
127
127
127
128

Figure 5

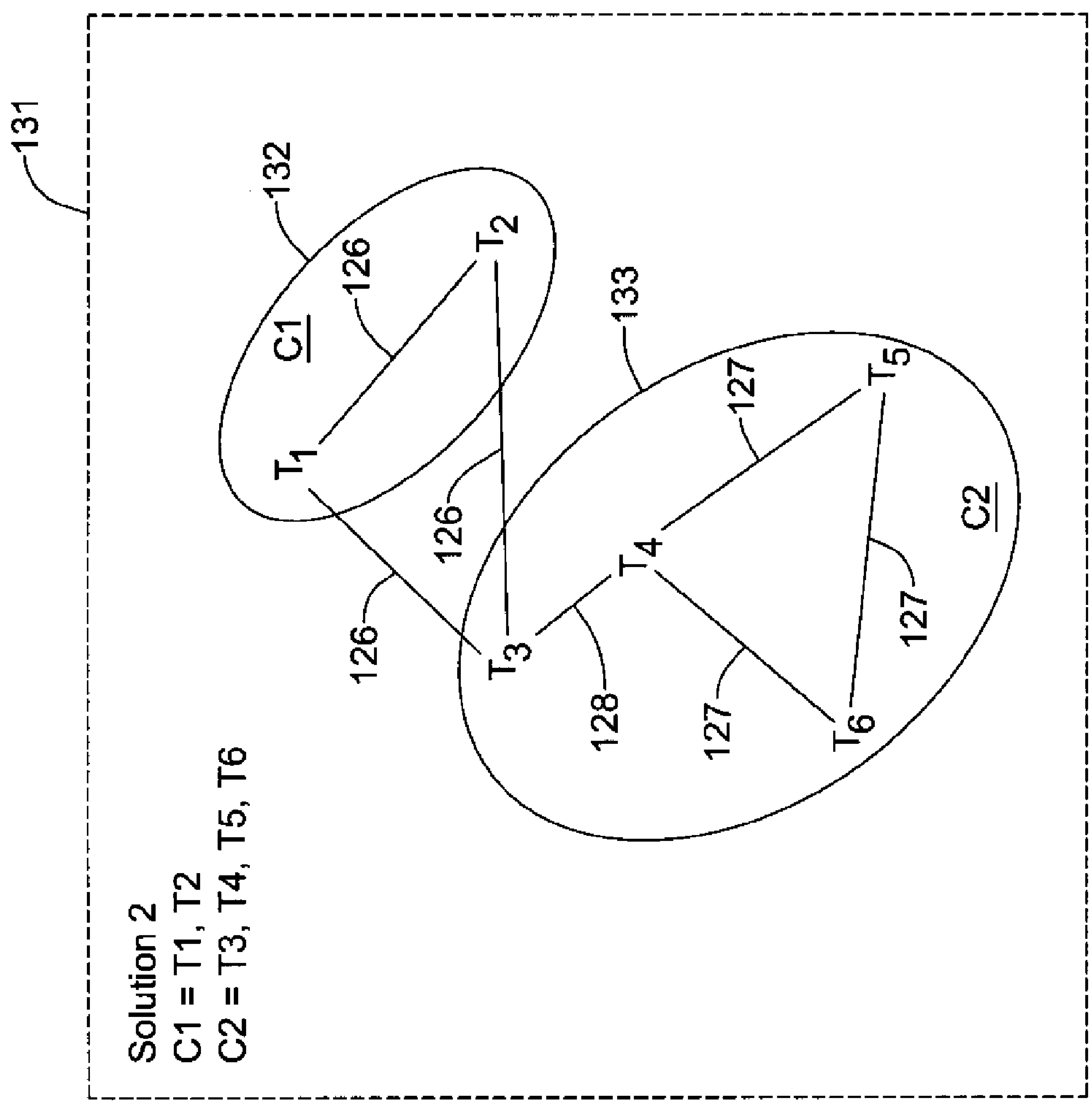
Solution 2
C1 = T1, T2
C2 = T3, T4, T5, T6
131
132
133
C1
C2
T_1
T_2
T_3
T_4
T_5
T_6
126
126
126
126
127
127
127
127
128

Figure 6

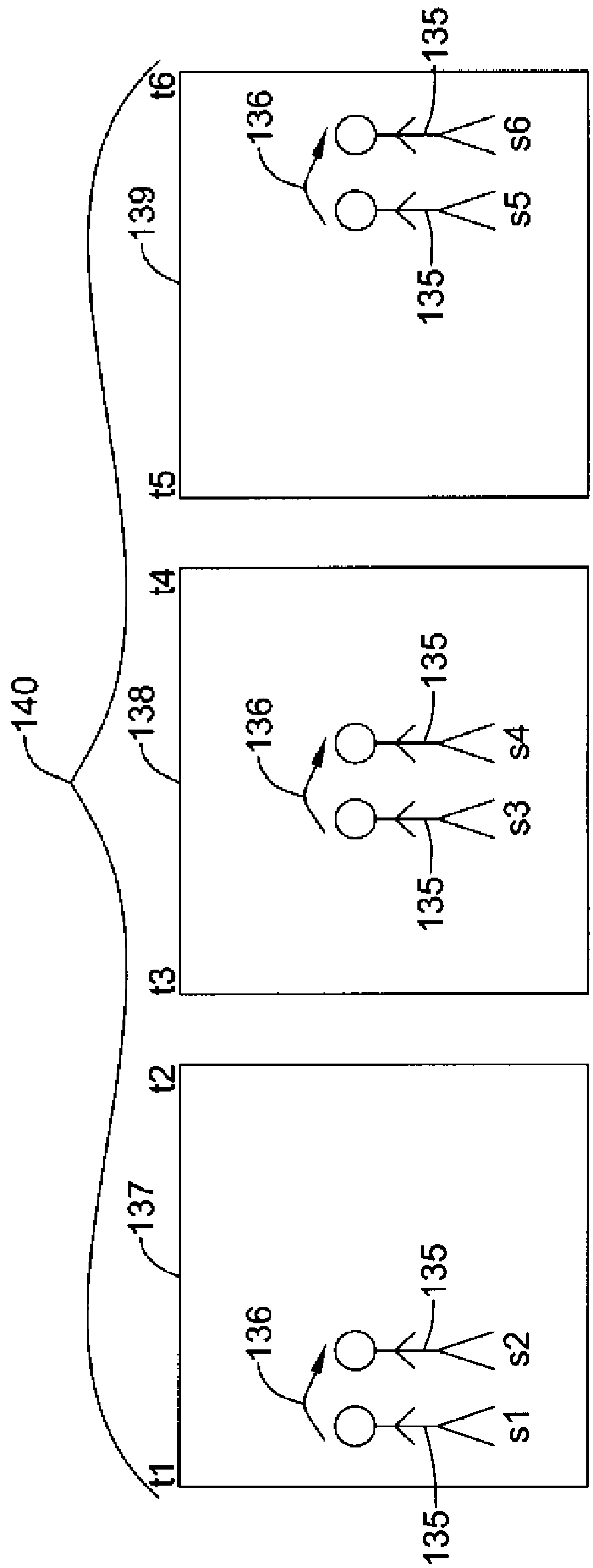

Figure 7

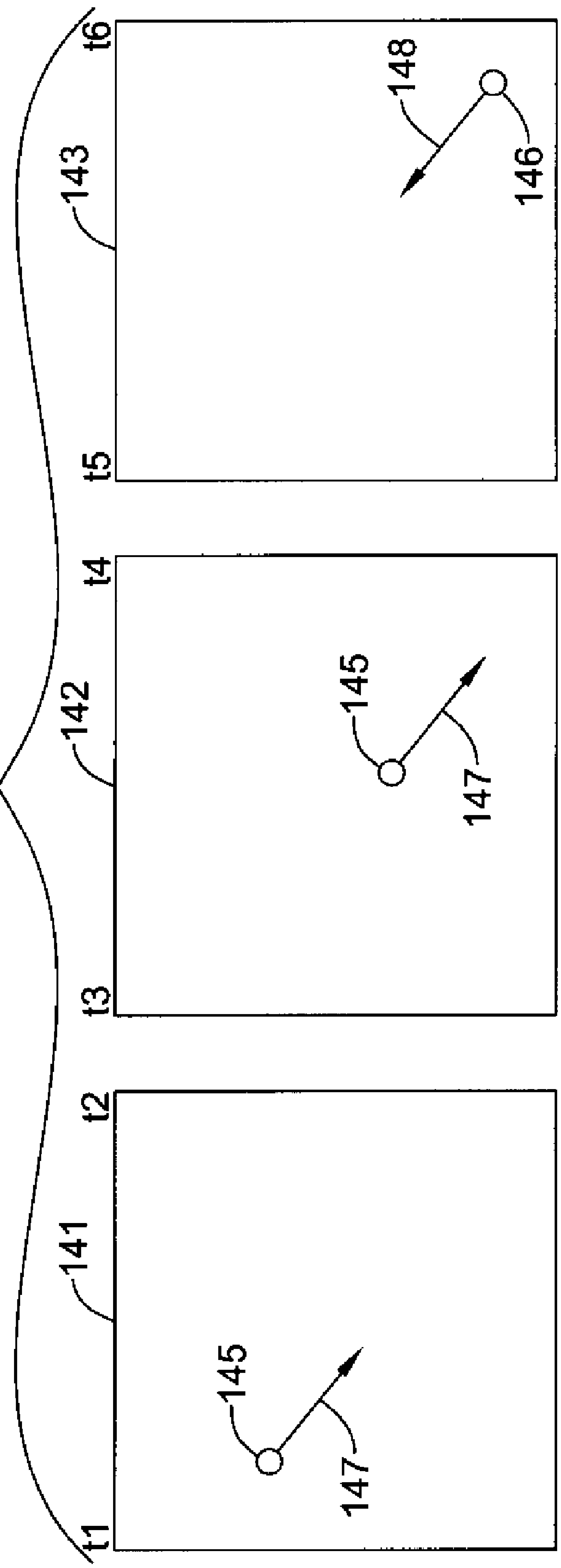

Figure 8

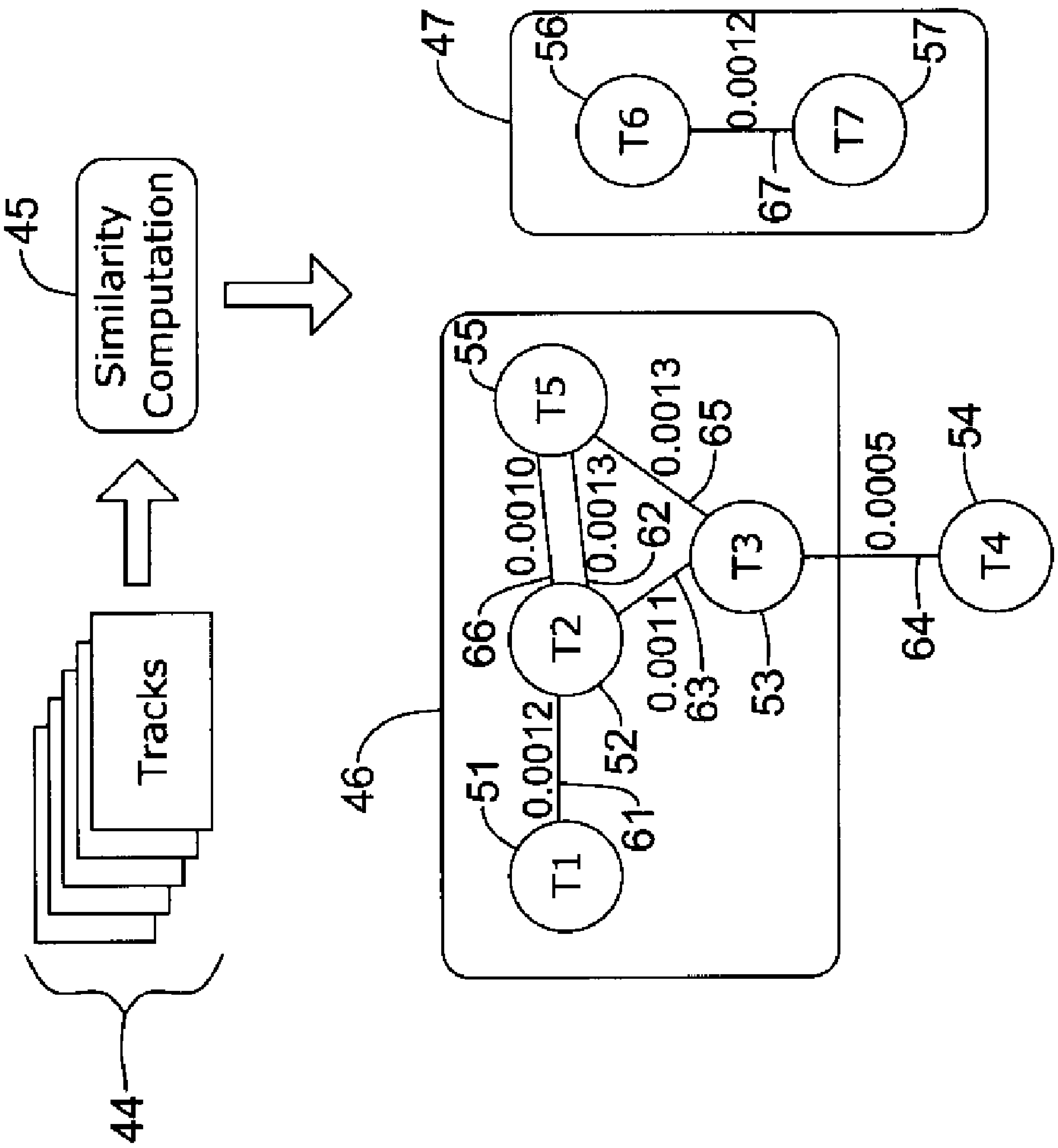
Tracks
Similarity Computation
44
45
46
47
T1
T2
T3
T4
T5
T6
T7
0.0012
0.0010
0.0013
0.0011
0.0013
0.0005
0.0012
51
52
53
54
55
56
57
61
62
63
64
65
66
67

Figure 9

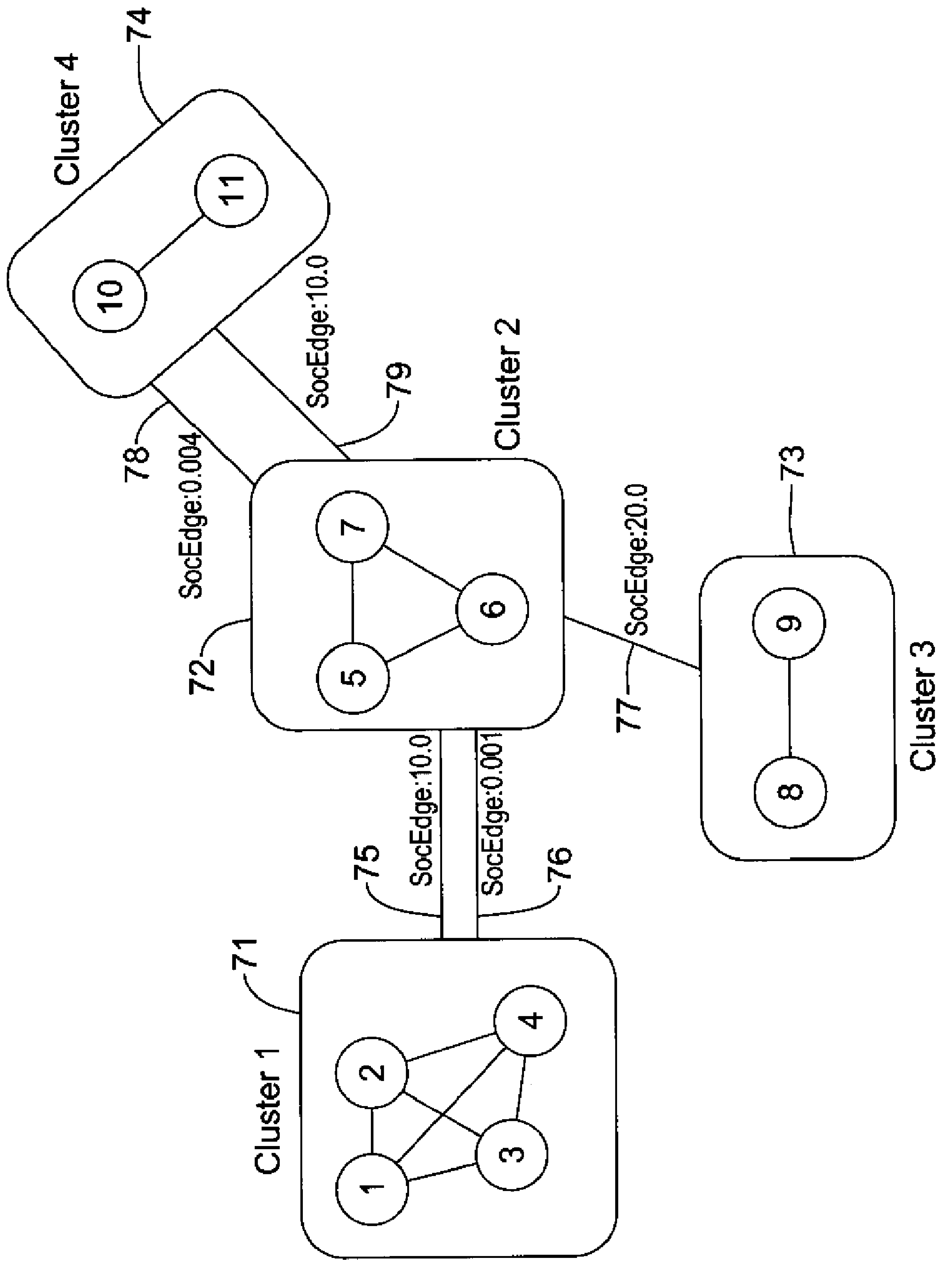
Cluster 4
74
10
11
SocEdge:10.0
79
Cluster 2
78
SocEdge:0.004
7
6
5
72
SocEdge:20.0
73
9
8
77
Cluster 3
SocEdge:10.0
SocEdge:0.001
75
76
71
Cluster 1
1
2
3
4

Figure 10

SYSTEM FOR INFORMATION DISCOVERY IN VIDEO-BASED DATA

BACKGROUND

The invention pertains to discovery of information from video data, and particularly to finding items disclosed in the information. More particularly, the invention pertains to determining relationships among the items.

SUMMARY

The invention is a system for information discovery of items, such as individuals or objects, from video-based tracks. The system may compute similarities of characteristics of the items and present the results in a matrix form. A similarity portrayal may have nodes representing the items with edges between the nodes. The edges may have weights in the form of vectors indicating similarities of the characteristics between the nodes situated at the ends of the edges. The edges may be augmented with temporal and spatial properties from the tracks which cover the items. These properties may play a part in a multi-objective presentation of information about the items in terms of a negative or supportive basis. The presentation may be partitioned into clusters which may lead to a merger of items or tracks. The system may pave a way for good group discovery in things like video-based social networks.

BRIEF DESCRIPTION OF THE DRAWING

FIG. **1** is a flow diagram of the present system;

FIG. **2** is a diagram of similarity matrix;

FIG. **3** is a diagram of node, edges and corresponding vectors;

FIG. **4** is a diagram of a number of tracks of two persons as indicated by edges between pairs of tracks and a line enclosures;

FIGS. **5** and **6** are diagrams of two different solutions of clustering of tracks;

FIG. **7** is a diagram of a series of frames of a track tending to indicate the same person in all of the frames;

FIG. **8** is a diagram of a series of frames of a track tending to indicate not the same person in all of the frames;

FIG. **9** is a diagram of a partitioning approach for track grouping for phase one clustering; and

FIG. **10** is a diagram of a network analysis for phase two clustering.

DESCRIPTION

A key challenge that needs to be addressed by nodal video data analysis is to enable robust cross-data analysis in the presence of node ambiguity. This may be due to the uncertainty that typically results from tracking entities in the presence of occlusions, stops and spatial and temporal gaps.

A crucial step is node disambiguation, which correlates subjects across cameras and time (e.g., if a subject leaves the view of a camera and later returns). This step may be crucial to enable integrated data mining or analyses across time and space. The primary means one may use to correlate subjects is to compare results of a face and/or body similarity computation. Given two images of subjects, the similarity computation may compute a score that specifies how similar the two images are. Therefore, if a single image is compared against all other images in the image database, an ordered list of images may be generated for it.

The similarity computation may have a number of disadvantages. First, due to the non-linear nature of the computation, only order can be derived from the results, but not comparative magnitude. E.g., assume image A is compared to images B and C and results in similarity metrics of 10 and 20, respectively. It does not necessarily follow then that B is twice as likely as C to be a match to A. While B is more similar to A than C, nothing more can really be said regarding the relative similarity. Another disadvantage is that general threshold values cannot necessarily be used across images. E.g., one cannot necessarily create a static rule that any pair of images with a similarity score over one hundred are to be considered different subjects. For some images, one hundred may be a good score. For others, it may be a poor match. Therefore, using only a similarity measure between images may be insufficient for node disambiguation.

The present invention is based on the following observations. The same subject cannot be observed in different places at the same time. In order for a subject to be observed at different locations, the time to travel to that location should be sufficient. Two tracks of similar subjects are more likely to belong to the same person if they are (almost) contiguous. That is, it appears more advantageous to cluster two similar tracks if they are also similar in time and space then to cluster two similar tracks that are not close in time and space.

The present node disambiguation approach may rely on multi-objective partitioning algorithms to cluster together tracks that are likely to represent the same person that a company, such as Honeywell International Inc., may apply to multi-modal data arising from a video recognition domain, including face and body similarity data, kinematic data, archived social network data, and so forth, to detect, correlate, and disambiguate individuals and groups across space and time.

One may use exclusivity constraints to indicate that two nodes may not refer to the same subject. Subjects that are observed at different locations at about the same time may not necessarily be clustered together. In addition, subjects observed at different location may not necessarily be clustered together if the temporal gap between observations is not sufficient for the subject to travel from one location to another.

Additionally, the similarity weights to connect two subjects may be dynamically adjusted based on temporal and spatial proximity. The more closely in time and space the subjects are the more importance one may put on similarity of those two subjects. Thus, the subjects observed over large temporal and spatial gap should only be clustered together if their similarity measure is extremely strong.

Multi-objective graph partitioning may compute clusters given graphs that have multiple types of edge and nodes, whose edge weights cannot be meaningfully combined.

Information in a graph may also or instead be in a form of a portrayal, rendition, presentation, depiction, layout, representation, or the like.

FIG. **1** is a flow diagram **80** of the present system. For illustrative purposes, six tracks (more or less) may be provided to symbol **82** for similarity computation. A track **81** may be a video sequence of a person or object. A track may be multiple frames of the same video. In diagram **80**, symbols with rounded corners may indicate a process or activity. Symbols with square corners may indicate a result or product of a preceding process or activity. An output of the similarity computation **82** may be a set of similarity matrices **83**, perhaps one for each characteristic to be compared among several persons listed in the axes of each matrix. The matrices **83** may be converted into a similarity graph **85** which may be regarded as a graphical representation of the matrices **83**. Each person may be a node. The nodes may be connected by edges. The edges may have vectors show a weight for each characteristic comparison between the nodes. Examples of characteristics may be face, body and gait. The strength of each similarity may be determined with a weight number. Another comparison may include spatial and temporal properties. These numbers corresponding to weights are not simply added up to determine overall similarity for clustering. Besides a weight number or indicator, there may be a factor of importance which is multiplied with each respective characteristic weight. For instance, the factors for face, body and gait similarities may be 10, 1 and 1, respectively. The factor for spatial and temporal properties may be 3. An algorithm may be designed to take in the weights and factors and calculate and determine clusterability of two (more or less) tracks, items, persons or nodes.

After the similarity graph **85** construction, a graph augmentation at symbol **86** may bring in the track special and temporal properties and tie them into the graph already having vectors for the characteristics. A result may be a multi-objective graph **87** of the items, tracks, nodes or persons in a form of vector edges with the characteristics in terms of similarity values between the nodes. A multi-objective graph partitioner **88** may take the values of the edge vectors and determine which nodes belong in the same cluster with a similarity score calculated by an algorithm. The result may be clusters **89**. From these cluster **89** indications, tracks **81** may be a merge track process **90** accordingly resulting in merged tracks **91**.

In flow diagram **80**, similarity computation **82** and similarity matrix may be in a similarity module **101**. Graph constructor **84** and similarity graph **85** may be in a graph module **102**. Graph augmentation **86** and multi-objective graph **87** may be in an augmentation module **103**. Multi-objective graph partitioner **88** and clusters **89** may be in a cluster module **104**. Merge tracks **90** may be a merger module **90**.

FIG. **2** is a diagram of similarity matrix **83**. The matrix may list items (e.g., persons) P**1**-P**9** on two axes of the matrix. The numbers may be weights of similarity of a characteristic between any two of the items listed. There may be a matrix **83** indicating weights of similarities for each characteristic among the items listed. For instance there may be a matrix for similarities of faces, a matrix for bodies, a matrix for gaits, and so on.

FIG. **3** is a diagram of nodes P**1**, P**2**, P**3** and P**4**. There may be an edge **106** between P**1** and P**2**, an edge **107** between P**2** and P**3**, and an edge **108** between P**1** and P**4**. The may be edges **109** and **111** between P**3** and P**4**. Weights may be associated with each of the edges. The weights may be expressed in a form of vectors **112**, **113**, **114** and **115** for edges **106**, **107**, **108**, and **109**, respectively. The numbers in vector boxes represent similarities of the face, body, gait, and spatial and temporal properties between each pair of the nodes connected with the respective edges. Vector **115** indicates a negative association of a −0.5 of the spatial and temporal properties as indicated by a line **111**. This may indicate that P**3** and P**4** cannot possibly have any association due to spatial or temporal conflicts. The numbers in the vector **115** box are zeros meaning that there are no similarities with the characteristics face, body or gait between P**3** and P**4**.

FIG. **4** is a diagram of tracks T**1**-T**6**. T**1**, T**2** and T**3** may be shown to be tracks of a person **1** as indicated by edges **119** and a line enclosure **117**. T**4**, T**5** and T**6** may be shown to be tracks of a person **2** as indicated by edges **121** and a line enclosure **118**. An edge between T**2** and T**4** may reveal some association of person **1** and person **2**.

FIG. **5** is a diagram of a solution **1** as indicated by a symbol **123** of clusters **124** (C**1**) and **125** (C**2**). Edges **126** may indicate similarities between T**1** and T**2**, T**2** and T**3**, and T**3** and T**1**, which is a basis for clustering T**1**, T**2** and T**3**. Edges **127** may indicate similarities between T**4** and T**5**, T**5** and T**6**, and T**6** and T**4**, which is a basis for clustering T**4**, T**5** and T**6**. An edge **128** may indicate similarities between T**3** and T**4**, which is a basis for associating clusters **124** and **125**.

FIG. **6** is a diagram of a solution **2** as indicated by a symbol **131** of clusters **132** (C**1**) and **133** (C**2**). Tracks T**1**, T**2**, T**3**, T**4**, T**5** and T**6** may have edges **126**, **127** and **127** like those in solution **1** (symbol **123**). In solution **2**, T**1** and T**2** form a cluster **132** (C**1**) and T**3**, T**4**, T**5** and T**6** form a cluster **133** (C**2**). The tracks and edges may be similar but the solution is different. Two edges **126** and **128** indicate a basis for associating clusters **132** and **133**. The solution that is preferred may be dependent upon the particular values of the edge weight vectors associated with edges **126** and **128**.

FIG. **7** is a diagram of three frames of a video track **140** of apparently the same person. Frame **137** shows a person **135** moving from one place to another on the left side of the frame during a period from t**1** to t**2** as indicated by the motion arrow **136**. Frame **138** shows a person who appears to be person **135** moving from one place to another at the center of the frame during a period from t**3** to t**4** as indicated by the motion arrow **136**. Frame **139** shows a person who appears to be person **135** moving from one place to another on the right side of the frame during a period from t**5** to t**6** as indicated by the motion arrow **136**. The spatial and temporal properties indicate the person in all of the frames to be the same one. This is because t**2** and t**3** are in temporal proximity and t**4** and t**5** are in temporal proximity and s**2** and s**3** are in spatial proximity and s**4** and s**5** are in spatial proximity. This may indicate a relatively large value in the element of the associated edge weight vector that represents spatial and temporal properties. Also noted are location marks s**1** and s**6** of person **135**.

FIG. **8** is a diagram of three frames of a video track **144** of arguably the same person. Frame **141** shows a person **145** moving in a direction from left to right on the left side of the frame during a period from t**1** to t**2** as indicated by a vector **147**. Frame **142** shows a person who appears to be person **114** moving from left to right at about the center of the frame during a period from t**3** to t**4** as indicated by vector **147**. Frame **139** shows a person who could be person **145** but appears to be a person **146** moving from right to left on about the right side of the frame during a period from t**5** to t**6** as indicated by a vector **148**. The spatial, temporal, and kinetic properties indicate that the person in frame **143** is different than the person in frames **141** and **142** due to the sudden change in movement direction. This may indicate a negative value in the element of the associated edge weight vector that represents spatial and temporal properties.

FIG. **9** is a diagram of a partitioning approach for track grouping for phase **1** clustering. A goal of phase **1** is to cluster tracks over short time frames. A group of tracks **44** may be provided for a similarity computation at block **45**. The relation may be a not all-to-all. There may be a negative association based on temporal locality and temporal constraints. From block **45**, similarity results may be used to construct similarity graphs **46** and **47**. The tracks T**1**, T**2**, T**3**, T**4**, T**5**, T**6** and T**7** may be nodes **51**, **52**, **53**, **54**, **55**, **56** and **57**, respectively. Edges **61**, **62**, **63**, **64**, **65**, **66** and **67** may be similarity scores between the nodes. Edge **61** may show a similarity score 0.0012 between nodes **51** and **52**. Edge **62** may show a similarity score 0.0013 between nodes **52** and **55**. Edge **63** may show a similarity score 0.0011 between nodes **52** and **53**. Edge **64** may show a similarity score 0.0005 between nodes

53 and 54. Edge 65 may show a similarity score of 0.0013 between nodes 53 and 55. An additional edge 66 may be added between nodes 52 and 55, based on temporal, spatial, and/or kinetic locality. Edge 66 may show a similarity score of 0.0010. The cluster score for graph 46 may be 0.00098. The cluster score is total internal edge weight divided by the number of possible edges. Other cluster metrics may be used such as the total internal edge weight divided by the number of nodes in the cluster. Graph 47 may be a recursively partition graph based upon spatial, temporal constraints and threshold cluster scores. An edge 67 may show a similarity score of 0.0012 between nodes 56 and 57. The cluster score for graph 47 is 0.0012.

FIG. 10 is a diagram of a network analysis for phase 2 clustering. A goal of phase 2 is to cluster spatially and temporally distant tracks. Multi-objective graph or portrayal partitioning may be applied to further cluster clusters-of-tracks into super clusters. Multi-objective graph or portrayal partitioning may also compute clusters, given diagrams or presentations that have multiple types of edges whose edge weights cannot necessarily be meaningfully combined. Clusters 71, 72, 73 and 74 are shown. Each cluster may be one of the tracks which are nodes with edges between them, as illustrated in FIG. 9. The clusters may have edges between which reveal inter-cluster similarity (SimEdge) and social relation (SocEdge) scores. A social relation may indicate that an association is likely based on pre-existing social network data. The social edge 75 score between cluster 71 and cluster 72 may be 10.0. The similarity relation score at edge 76 between clusters 71 and 72 may be 0.001. The social relation score at edge 77 between clusters 72 and 73 may be 20.0. The similarity score at edge 78 between clusters 72 and 74 may be 0.004. The social score at edge 79 between clusters 72 and 74 may be 10.0.

The following applications may be relevant. U.S. patent application Ser. No. 12/547,415, filed Aug. 25, 2009, and entitled "Framework for Scalable State Estimation Using Multi Network Observations", is hereby incorporated by reference. U.S. patent application Ser. No. 12/369,692, filed Feb. 11, 2009, and entitled "Social Network Construction Based on Data Association", is hereby incorporated by reference. U.S. patent application Ser. No. 12/187,991, filed Aug. 7, 2008, and entitled "System for Automatic Social Network Construction from Image Data", is hereby incorporated by reference. U.S. patent application Ser. No. 12/124,293, filed May 21, 2008, and entitled "System Having a layered Architecture for Constructing a Dynamic Social Network from Image Data", is hereby incorporated by reference.

In the present specification, some of the matter may be of a hypothetical or prophetic nature although stated in another manner or tense.

Although the present system has been described with respect to at least one illustrative example, many variations and modifications will become apparent to those skilled in the art upon reading the specification. It is therefore the intention that the appended claims be interpreted as broadly as possible in view of the prior art to include all such variations and modifications.

What is claimed is:

1. An information discovery network system comprising: one or more cameras;

a track module for obtaining video-based tracks, the tracks having a first number of items;

a similarity module connected to the track module, the similarity module computes similarities among characteristics of the first number of items within the tracks and provides a similarity matrix for each characteristic of the characteristics using the computed similarities;

a portrayal module connected to the similarity module, the portrayal module for constructing a similarity portrayal having nodes representing the items with edges between the nodes having weights in a form of vectors indicating similarities of the characteristics of the items at ends of the edges;

an augmentation module connected to the portrayal module, the augmentation module providing a multi-objective portrayal by augmenting the edges of the similarity portrayal with temporal and spatial properties from the tracks covering the first number of items;

a cluster module connected to the augmentation module, the cluster module for partitioning the multi-objective portrayal into clusters; and

a merger module connected to the cluster module and the track module, the merger module for merging the tracks according to the clusters from the track module; and wherein a multi-objective partitioning algorithm determines a cluster threshold based on the weights of a vector of the vectors to determine whether the items of an edge are to be clustered with each other;

a weight of said each characteristic of the characteristics is multiplied by a factor to result in a product; the factor is a number which is relative to an impact of a characteristic for a track; and products of the weights of the characteristics and the spatial and temporal properties, and factors are determinate of an importance of an edge for clustering.

2. The system of claim 1 wherein the merger module outputs a second number of merged tracks.

3. The system of claim 2, wherein the first number is equal to or greater than the second number.

4. The system of claim 1, wherein the cluster module determines clusters with a multi-objective partitioning algorithm that incorporates weights at the edges indicating similarities of the characteristics of the items represented by the nodes proximate to the edges.

5. The system of claim 4, wherein a number of clusters from the cluster module determines the second number of merged tracks.

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